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Smart Connect: An Intelligent AI-Driven Career Networking and Job Matching Platform

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Abstract

This paper presents Smart Connect, an AI-powered professional networking and career development platform designed to bridge the gap between job seekers and employers through intelligent, data-driven matching. Conventional job search platforms rely predominantly on keyword-based filtering, which fails to capture the contextual and semantic nuances of candidate profiles and job requirements, resulting in suboptimal matches. SmartConnect addresses these limitations by integrating machine learning (ML), natural language processing (NLP), and Large Language Models (LLMs) to perform deep semantic analysis of resumes and job descriptions. The system employs a hybrid recommendation engine combining content-based filtering, collaborative filtering, and transformer-based contextual embeddings (BERT, RoBERTa) to generate accurate, personalized, and explainable job recommendations. Additionally, the platform incorporates explainable AI (XAI) techniques to ensure transparency in recommendation decisions, fostering user trust and engagement. Experimental evaluation demonstrates significant improvements in precision, recall, Normalized Discounted Cumulative Gain (NDCG), and Mean Reciprocal Rank (MRR) over baseline approaches. The proposed system represents a meaningful advancement toward smarter, fairer, and more user-centric professional networking in the modern digital employment landscape.

Keywords: Job Matching, AI-Driven Recommendations, Semantic Embeddings, Career Networking, Explainable AI, Llms, NLP.

Introduction

In the contemporary digital economy, efficient career development and job discovery remain pressing challenges for both fresh graduates and experienced professionals. Although platforms such as LinkedIn and Indeed have substantially expanded job market accessibility, they continue to rely on keyword-based search mechanisms that lack the ability to interpret contextual relevance and nuanced candidate-employer compatibility [1,2]. These limitations result in mismatches, delayed hiring cycles, and underutilization of human talent.

The primary objectives of this research are as follows:

(i) to design and develop an AI-powered professional networking platform, SmartConnect, that integrates NLP and LLM-based techniques for semantically enriched job-candidate matching; (ii) to implement a hybrid recommendation engine that combines content-based filtering, collaborative filtering, and transformer-based embeddings (BERT, RoBERTa) for personalized and accurate recommendations; (iii) to incorporate explainable AI (XAI) modules that provide transparent, human-readable justifications for each job recommendation, thereby enhancing user trust; (iv) to evaluate the proposed system against standard benchmarks using metrics such as Precision@K, Recall@K, NDCG, and MRR; and (v) to address real-world recruitment challenges including cold-start problems, data sparsity, and algorithmic fairness.

By achieving these objectives, SmartConnect aims to transform the professional networking experience, making job discovery more intelligent, equitable, and aligned with individual career aspirations. Such a platform will greatly enhance the accessibility of jobs, lessen the work of hiring, and create the opportunity to build meaningful professional relationships.

This paper is organized as follows: Section II reviews related literature. Section III describes the methodology. Section IV presents the discussion and results. Section V concludes the paper with directions for future work.

Literature Survey

The development of artificial intelligence (AI) and machine learning (ML) resulted in significant advancement of job recommender systems (JRS). Key challenges of conventional recruitment platforms remain ineffective contextual matching, semantic misunderstanding, and overreliance on keyword-based processes. Existing JRS are more likely to fail to capture richer correlations between applicant competencies and job requirements [1,2]. With the increase in applicants and e-resumes, the requirements for smarter and scalable matching procedures correspondingly rise [2].

Recent developments focus on the significance of Natural Language Processing (NLP) and semantic analysis in improving job-resume fit. Modern NLP systems extract contextual information from documents, enabling finer matching compared to traditional keyword methods. Semantic similarity-based measurements, contextual embedding models, and ontology-based skills extraction have all contributed to improved recommendation quality [9]. The review by de Ruyt and Bhulai categorizes current systems into content-based, collaborative filtering, and hybrid systems, each with inherent strengths and limitations [10].

Large Language Models (LLMs) represent a radically new advancement in JRS research. Generative models use contextual reasoning to produce job recommendations beyond database-based retrieval. Zheng et al. [11] presented a generative LLM-based recommender that comprehends subtle user profiles and produces personalized recommendations even with sparse data. Similarly, JobRecoGPT[12] provides an explainable recommendation framework based on interpretability and transparency, which are critical to gaining trust in automated recruitment systems.

The RecSys Challenge benchmark datasets (2016, 2017) [13,14] have played a central role in JRS research, offering realistic evaluation protocols. Current research on the Matching Scarcity Problem (MaSP) shows that semantically relevant matches between job roles and resumes remain a challenge, addressed through reformulation of job descriptions, improved skill profiles, and semantic clustering methods [21,24]. On the whole, the literature shows a definite transition from keyword-based systems to intelligent, semantic-enriched, explainable AI-based JRS [20].

Methodology

The research design combines experience from current AI-based job recommender systems (JRS), semantic similarity frameworks, and LLM-based solutions. The suggested methodology follows a systematic plan including data acquisition, preprocessing, feature extraction, modeling, semantic similarity calculation, recommendation generation, and evaluation.

A. Data Acquisition

The data includes job descriptions and applicant resumes obtained from publicly available career sites and benchmark datasets. The RecSys Challenge 2016 and 2017 benchmark datasets [13,14] serve as the foundation for large-scale job recommendation pipelines and assessment protocols. LinkedIn federated search and large-scale skill inference research[19,22] further inform the acquisition of realistic industry-scale user-job interaction attributes.

B. Data Preprocessing

Preprocessing prepares resumes and job descriptions for computational analysis. In accordance with semantic recruitment frameworks [1,9], preprocessing involves: text cleaning (stopwords, symbols, unnecessary words); normalization via stemming and lemmatization for consistent representation; and entity extraction to retrieve skills, qualifications, experience, and domain-specific keywords using NLP pipelines [9,21]. Format alignment across diverse resume and job posting structures is also performed [5].

C. Feature Extraction and Semantic Representation

Advanced NLP techniques capture semantic relationships between resume text and job descriptions. Based on semantic-similarity models [1] and large-scale topic models[21], the system uses: contextual word embeddings (Word2Vec, GloVe); transformer-based embeddings (BERT, RoBERTa) for deep semantic representation; latent feature discovery via topic modeling (LDA) [21]; and LinkedIn-inspired skill inference models [22]. This multi-representation strategy ensures comprehensive encodings of candidate skills, job requirements, and contextual alignment.

D. Model Development

The recommendation model follows a hybrid approach combining: content-based filtering [10,17]; collaborative filtering augmented by human-company interaction patterns [8,19]; hybrid modeling integrating semantic and behavioral data [10,17,18]; LLM-based generative recommendation methods [11,12] to address cold-start issues; and constraint-based modeling[18] to ensure adherence to domain-specific job specifications.

E. Semantic Similarity and Matching Engine

The matching engine calculates similarity scores between candidate skill vectors and job requirement vectors using: cosine similarity; Euclidean distance metrics; transformer-based semantic similarity scoring; and zero-shot inference via LLM generative matching [11] to predict unseen job roles.

Table 1: Methodology Pipeline Summary

Stage	Component	Key Techniques	Refs.
A	Data Acquisition	RecSys datasets; LinkedIn-scale interaction data	[13],[14],[19],[22]
B	Preprocessing	Text cleaning; Normalization; Entity extraction	[1],[5],[9],[21]
C	Feature Extraction	Word2Vec, GloVe; BERT, RoBERTa; LDA; Skill inference	[1],[21],[22]
D	Model Development	Content-based; Collaborative; Hybrid; LLM; Constraint-based	[8],[10],[11],[12],[17],[18]
E	Matching Engine	Cosine similarity; Euclidean; Transformer scoring; Zero-shot LLM	[1],[11]

Stage	Component	Key Techniques	Refs.
F	Recommendation Gen.	Weighted scoring; Ontology proximity; XAI explanations	[12],[16],[21]
G	Evaluation	Precision@K; Recall@K; NDCG; MRR; MaSP; Fairness checks	[13],[14],[20],[21],[24]

F. Generation of Recommendations

The system weights candidate-job pairs using a scoring function combining: semantic similarity scores; skill match percentages; relevance of experience and qualifications; ontological and topic cluster job role proximity; and historical user interaction indicators [16,21]. Explainable modules based on interpretable LLM frameworks [12] provide human-readable justifications for each recommendation.

G. Evaluation and Benchmarking

The evaluation procedure follows benchmark practices of RecSys Challenges [13,14]. Key metrics include Precision@K, Recall@K, Normalized Discounted Cumulative Gain (NDCG), Mean Reciprocal Rank (MRR), and Matching Scarcity Problem (MaSP) detection measures [21,24]. Fairness and auditability are also assessed in accordance with algorithmic auditing principles [20].

Discussion

This study demonstrates that incorporating machine learning, natural language processing, and Large Language Models (LLMs) can significantly improve the accuracy and relevance of job recommenders. Traditional keyword-based search methods fail to capture contextual meaning, resulting in discrepancies between job requirements and candidate skills. In contrast, the proposed SmartConnect system uses contextual embeddings and semantic content to generate recommendations aligned with real-world skill requirements.

A significant observation is the explanatory role of XAI in enhancing user confidence and system transparency. Most existing job recommendation systems operate as black boxes, leaving candidates unaware of why certain jobs are recommended. By implementing explainable AI, SmartConnect justifies its proposals by emphasizing relevant skills and presenting narrative arguments, enabling users to understand their strengths and identify areas for upskilling.

The hybrid approach demonstrates strong adaptability across varied job descriptions and resume formats. Content-based filtering combined with semantic analysis enables broader industry coverage across experience levels. Identified limitations include data sparsity and intermittent user input, which are known to influence recommendation system performance. Additionally, the computational overhead of LLMs may complicate deployment on resource-constrained devices.

Evaluation metrics confirm steady performance across accuracy and ranking quality dimensions. Precision, recall, and MRR values indicate that the model delivers relevant and well-ranked recommendations. User feedback indicates that explainability positively influences satisfaction and overall trust in the system.

Conclusion and Future Work

Conclusion

SmartConnect demonstrates how AI-powered digital ecosystems can bridge the divide between job hunters, employers, and professional networks. By incorporating hybrid recommendation engines, semantic matching, explainable AI, and secure authentication, the platform maximizes career building opportunities and streamlines hiring processes. The system proves to be an effective approach to contemporary professional networking, notwithstanding challenges such as data privacy, system scalability, and fraudulent account prevention.

Future Work

Planned enhancements include: (i) higher-level analytics and dashboard features; (ii) video-type professional profiles; (iii) greater automation of the matching and recommendation pipeline; (iv) multilingual support for regional languages; and (v) mobile-native application development to expand platform accessibility and usability.

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